Digital Twin and Blockchain Technology Empowered by AI: a New Paradigm for Sustainable Ship Spare Part Logistics

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Abstract. In maritime supply chain management, challenges such as material traceability, environmental sustainability, and economic efficiency significantly hinder effective materials management and limit the opportunities for recycling and reusing ship components. This study presents a framework that integrates blockchain technology (BT), smart contracts (SC), and artificial intelligence (AI) to address critical challenges in maritime supply chain management, such as material traceability, environmental sustainability, and economic efficiency. This framework represents a precursor to a more complex and advanced development. The main objective of the study is to analyze existing technologies and evaluate how they can be implemented more efficiently and practically in the maritime sector. The framework enhances the lifecycle management of ship components, promotes circular economy practices, and improves overall logistics operations. The integration of digital twin (DT) technology further supports real-time monitoring and decision-making, creating a scalable and adaptable ecosystem that optimizes resource use and maximizes residual value. The research outlines the potential benefits and practical implementation challenges of this advanced digital framework in the maritime sector, offering a pathway toward more sustainable and efficient supply chains.

Keywords: Digital Twin, Blockchain Technology, Artificial Intelligence, Smart Contracts, Circular Economy, Maritime Supply Chain.

1 Introduction

Ships, as intricate systems, necessitate continuous oversight to maintain maritime safety and efficiency. To meet this demand, sophisticated computerized tracking and monitoring systems have been created to handle various stages of a ship's lifecycle, from its design and daily operations to its eventual dismantling and recycling. This emphasizes the critical role of thorough documentation in maritime transport (Okasha et al., 2010). Moreover, this complex operational framework mandates diligent information and metadata management involving multiple operators. Historically, the maritime sector has relied on preventative maintenance, dictated by fixed schedules for parts replacement or maintenance work. This strategy, however, often resulted in unnecessary downtime and costs, or equipment failures due to sparse maintenance intervals (Pahl, 2022). Currently, there is a shift towards proactive maintenance, facilitated by digital advancements and data analytics. Emerging technologies such as smart contract (SC), blockchain technology (BT), and digital twin (DT) are increasingly essential for enhancing the reliability and serviceability of maritime equipment (Farah et al., 2024; Taghavi & Perera, 2024). Technological innovations are significantly transforming the maritime sector by automating processes and enhancing large-scale transport infrastructure management. The integration of AI into maritime operations marks a significant advancement, with technologies like neural networks and algorithms enhancing navigational safety and operational efficiency. Over the past decade, these AI applications have become increasingly vital in addressing navigational and structural challenges in the industry. Figure 1 illustrates a comprehensive management system based on DT, which supports the entire lifecycle of ship components and materials tracked and evaluated from a circular economy and value creation perspective, enriched by AI and IoT data insights. Throughout their operational life, ships generate vast amounts of data. AI leverages this data to optimize operations and enhance environmental sustainability. By continuously processing and learning from this data, AI not only supports real-time decision-making but also anticipates future needs, enabling proactive maintenance and efficient resource utilization.

The main purpose of this work is to examine how emerging technologies can promote a circular economy in the maritime sector, enhancing sustainability and operational efficiency throughout the entire lifecycle of a ship, from design and construction to its

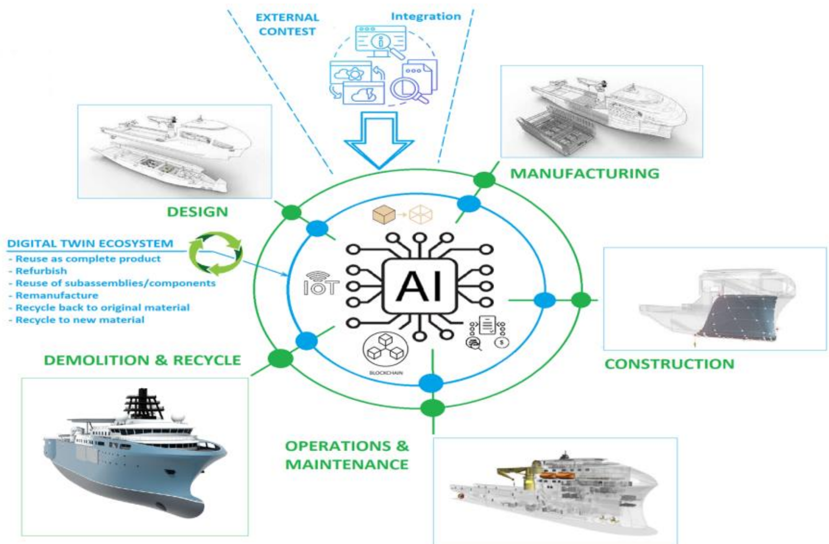

Figure 1 Digital Twins-based management system.

dismantling and recycling. The document aims to provide a clear overview of the opportunities and challenges associated with the adoption of these technologies, through a critical review of traditional maintenance strategies and an analysis of innovative solutions currently in development.
The article is organized as follows: the first section presents a literature review on the technologies contributing to the digitalization of the maritime sector. In the following sections, recent developments in the digitalization of the ship lifecycle will be analyzed. The focus will then shift to emerging technologies, such as smart contracts, blockchain, and digital twin, with an in-depth analysis of their potential impact on maritime operations management and navigational safety. Finally, the document concludes with a reflection on the future implications of these technologies for the sector, with particular emphasis on the use of AI and the formulation of a framework that can ensure efficiency in the shipping industry.

2 Literature Review

The primary objective of this literature review is to provide a comprehensive overview of the key technologies—digital passport (DP), BT, SCs, DTs, and predictive models—applied in the management of ship components. This review will elucidate how each technology contributes to enhancing operational efficiency, safety, and sustainability in the maritime industry. By synthesizing the current state of research and practice, this review aims to identify existing gaps and propose a unified framework that integrates these technologies for improved maritime asset management.

DPs are pivotal tools designed to promote product sustainability and lifecycle transparency. These digital documents serve as comprehensive repositories of a product's lifecycle information, from manufacturing to disposal, facilitating the traceability. In the maritime industry, DPs can record and manage detailed information about ship components, akin to the Digital Battery Passport (DBP) introduced in the battery industry. The DBP provides a standardized data model for tracking the lifecycle of batteries, capturing data on manufacturing processes, materials used, and recycling information. Similarly, a DP for ship components can include data such as material specifications, operational performance, and compliance with environmental regulations, thereby supporting circular economy initiatives (Gianvincenzi, Marconi, Mosconi, & Tola, 2024). In the literature, studies conceptualizing the development of a DP for the useful life of ships are limited. In maritime settings, studies like those by Adisorn et al., 2021, have explored frameworks for DPs that facilitate data sharing within the supply chain to support circular practices. Sterling, 2014, developed a related database for integrating material information into a ship's 3D model, improving material traceability.

BT is founded on the principles of immutability and decentralization. It operates as a distributed ledger that records transactions across multiple nodes in a network, ensuring that data, once recorded, cannot be altered retroactively. This characteristic of immutability enhances the security and trustworthiness of the data. Irannezhad, 2020 has delved into the use of BT in logistics and transportation, highlighting its potential to streamline process coordination, information sharing, and data security through encryption. Oloruntobi et al., 2023 examined the potential adoption of BT in global maritime container logistics, highlighting benefits for trading partners and shipping companies. Other researchers have explored BT applications in maritime logistics, focusing on trust issues within supply chains. Andersson & Leander Bachelor, 2019; Zhou et al., 2020. identified significant trust issues such as lack of communication, opportunistic behavior, distrust in information, and high interdependence among actors Loklindt et al., 2018; Tijan et al., 2019further evaluated the adoption of BT for shipping information exchange and proposed decentralized data storage solutions for the maritime sector.

SCs are self-executing contracts with the terms of the agreement directly written into code. They automatically execute and enforce the terms of a contract when predefined conditions are met, eliminating the need for intermediaries. This automation leads to increased efficiency, reduced costs, and enhanced reliability in executing contractual agreements. Study by Editors et al., 2023 shows that SCs can automate processes such as verifying goods receipts at ports, triggering actions like delivery confirmations and invoice generation. This not only streamlines financial operations but also ensures ongoing, real-time monitoring of cargo, which is vital in maritime logistics. Khalid et al., 2023 have demonstrated how SC code (chaincode) can be customized for the specific needs of maritime logistics, offering enhanced privacy and scalability. This customization is particularly advantageous for maritime businesses requiring a controlled, adaptable BT environment.

DTs are defined as virtual replicas of physical assets, systems, or processes that mirror their real-world counterparts in real-time. These digital models integrate data from various sources, including sensors (e.g. IoT), to simulate the physical asset's behavior, performance, and condition. The structure of a DT typically includes a digital model of the asset, real-time data inputs, and advanced analytics capabilities to provide insights and predictive maintenance recommendations(Madusanka et al., 2023). The benefits of such DT technology include enhanced safety (Sepehri et al., 2022) increased operational efficiency, less environmental impacts (Ang et al., 2017) and the sustainability of shipping operations, along with the potential for developing new and innovative business models within the shipping industry (Lambrou et al., 2019).

Machine learning (ML) techniques play a crucial role in predictive analytics, providing sophisticated tools for data analysis and forecasting across various sectors, including maritime operations. ML encompasses supervised learning methods like regression and classification, unsupervised learning such as clustering and dimensionality reduction, and reinforcement learning. These techniques analyze large datasets to identify patterns and predict future events effectively. In the maritime industry, ML is employed to anticipate maintenance requirements, optimize routing, and boost operational efficiency (Kaklis et al., 2023).. DTs benefit significantly from predictive models, as they use ML algorithms to process historical and real-time data, predicting the performance of ship components and systems. Case studies have shown that predictive models can accurately forecast the failure of critical components, preventing expensive downtime, and enhancing decision-making, reducing operational costs, and improving safety in maritime operations (Troupiotis-Kapeliaris et al., 2022)

The literature highlights several gaps in the use of advanced technologies in maritime operations. A key issue is the lack of a universal and adaptable data model for DPs, which impedes standardized application across different sectors (Gianvincenzi, Marconi, Mosconi, & Tola, 2024). The security and traceability of DTs also need enhancement, potentially through BT integration, to ensure data integrity and system reliability (Zheng & Tian, 2022). Furthermore, the precision of predictive models under extreme conditions is limited, necessitating improvements for effective use in complex maritime environments (Troupiotis-Kapeliaris et al., 2022).. There's also an absence of integrated frameworks that effectively combine DPs, BT, SCs, DTs, and predictive models, which limits the realization of their combined potential. Developing such frameworks is crucial for advancing the management of ship components and operations, as shown by early efforts like Hyundai's "Smart Ship" project and the "Smart Maritime Network" (Chen & Guedes Soares, 2021). A unified approach is proposed to optimize ship management and enhance maritime operations' efficiency, safety, and sustainability.

3 The Comprehensive Framework for Maritime Sector

This section outlines a comprehensive framework designed to enhance the management and lifecycle tracking of ship components by integrating advanced technologies. The framework utilizes digital DPs, BT, SCs, DTs, and predictive models to improve data transparency, regulatory compliance, operational efficiency, and environmental impact within the maritime industry. The primary goal is to ensure that ships are effectively monitored and managed throughout their lifecycle, preserving their intrinsic value. The framework is structured in layers, each with a specific role, to manage all phases from design and material acquisition to construction, operational management, maintenance, repair, and recycling. The layers are as follows:

- **Blockchain layer.** At the core of the framework, BT acts as an integrity enabler, securely immutable recording key historical evidence for transactions throughout the ship's lifecycle.
- **Computing layer.** It leverages data processing capabilities to define and characterize the DT, providing real-time or near real-time accounts of the system's conditions, such as maintenance and operational use.
- **Data management layer.** It includes the information management framework and user interfaces, enabling project participants to interact with the DT applications.
- **Connection layer.** It interfaces with the physical world through APIs and sensors, facilitating real-time data collection.

Figure 2 visually depicts the structure of the comprehensive framework, highlighting the cyclical nature of a ship's lifecycle—from design and manufacturing to operations, maintenance, demolition, and recycling. Each phase is interconnected by the flow of project data, supporting a circular economy. The framework is represented in layers: the blockchain layer (dark blue) ensures data integrity and traceability, the computing layer (purple) handles computational processes, the data management layer (blue) manages data handling and user interfaces, and the connection layer (green) manages physical data inputs and outputs.

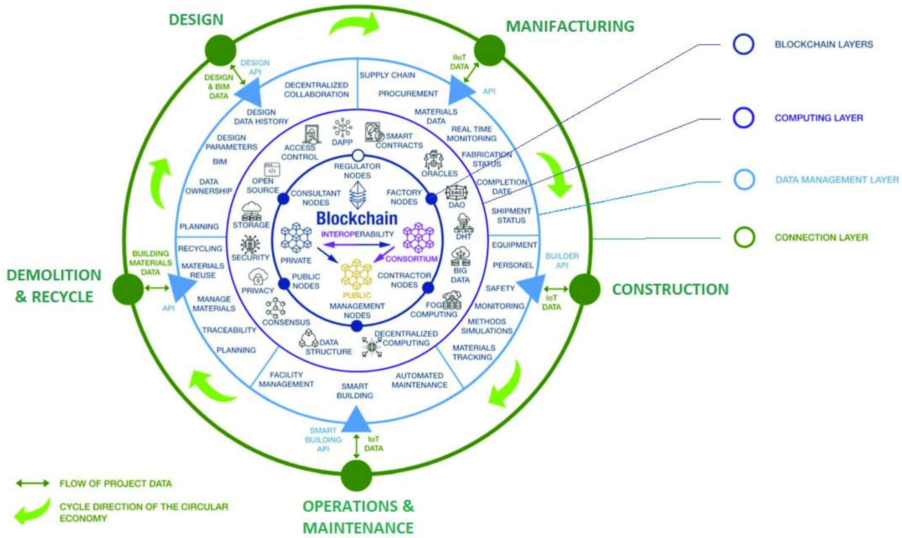

Fig. 2. The Framework Structure and layers representation.

The subsequent sections will detail each layer of the framework. The Blockchain Layer ensures data integrity, security, and transparency throughout the ship's lifecycle using BT. This layer integrates with the DP to facilitate effective tracking and management. Next, the Computing Layer manages and processes complex data using advanced computational techniques and AI to optimize lifecycle management, enhance operational efficiency, and ensure regulatory compliance. This layer builds on a structured data model to handle parameters derived from technological, legislative, and lifecycle analyses. The Data Management Layer (DML) collects, stores, manages, and analyzes data across all lifecycle phases, from design to demolition. Supported by the Computing and Connection Layers, the DML enables optimized operations, improved safety, and regulatory compliance. It handles data collection, archiving, access control, production planning, real-time monitoring, and integration with resource management systems. Finally, the Connection Layer facilitates communication between all components and systems throughout the ship's lifecycle. It ensures connectivity, real-time monitoring, and data integration to support predictive maintenance and operational efficiency. This layer integrates with the Computing Layer to provide the necessary computing power for data processing and predictive analytics. Each section will analyze the technologies involved, their integration within the framework, and their contributions to enhancing ship lifecycle management.

3.1 Blockchain Layer

The blockchain layer serves as the cornerstone of the framework, ensuring data integrity, security, and transparency throughout the ship's lifecycle. By leveraging BT, the framework records every transaction related to the ship's lifecycle in an immutable ledger. This layer addresses the challenges of traditional product lifecycle management systems, such as data silos, lack of transparency, and difficulties in ensuring data integrity. BT mitigates these issues, facilitating effective tracking and management of products throughout their lifecycle, which is critical for achieving sustainability goals and complying with regulations. To address the inherent challenges of traditional lifecycle management systems, such as data silos, lack of transparency, and data integrity issues, we propose integrating BT and SCs into the DP. This integration will enable immutable and transparent recording of all lifecycle events, from the construction to the decommissioning of ship components, ensuring comprehensive traceability and accountability. This proposed solution has been prototyped to test its effectiveness, demonstrating how its core features can overcome these challenges. The proposed system defines specific roles for different stakeholders to ensure a fully decentralized yet accessible and user-friendly DP management process. The key roles include:

- **Owner.** The entity that creates the DP and has primary control over its initial setup and registration. This role can operate in private, consortium, or public BT settings.
- **Updater.** Stakeholders responsible for updating the information in the DP. This can include manufacturers, operators, and recyclers who add or modify data as the product moves through its lifecycle.
- **Public and Private Stakeholders.** Entities such as regulatory bodies and the public can view the information in the DP for transparency and compliance purposes, while authorized entities such as maintenance providers and suppliers need access to specific data within the DP to perform their functions. This differentiation is based on the Battery Regulation (EU)2023/1542, which regulates the battery DP, including publicly accessible data points and different levels of data privacy to ensure that certain sensitive information is only accessible to authorized personnel.
- **Verifying Body.** An external entity responsible for verifying and validating the information contained in the DP to ensure its accuracy and compliance with relevant regulations.

The system workflow is designed to allow each actor to manage the data model, interact with the SC, and engage with the verifying body, ensuring a seamless and secure process, and maximizing decentralization. The use of an XML-based data model allows for flexibility, consistency, and interoperability, facilitating seamless data exchange and integration across various systems and stakeholders. This ensures that the data management process is robust, secure, and user-friendly, enhancing the overall efficiency and reliability of the lifecycle management system. The system workflow is the following:

Creation and Initialization. The Owner downloads the XML template and the digital tool from the verifier's platform. After entering the necessary information into the XML, the file is hashed using a selected hashing algorithm, and this hash is recorded on the BT via a SC. The SC ensures that only authorized updates are recorded and that each transaction is immutable. This interaction is managed through a digital interface that automates the process of hashing and BT transactions. Subsequently, the Owner re-uploads the XML to the verifier's platform, which automatically verifies the hash and saves it in its database.

Data Entry and Management. The Updater adds and modifies data within the XML file using a similar procedure. The Updater downloads the latest version of the XML related to the existing DP and uses the digital tool's function dedicated to updaters. The updated file is hashed, and the hash is recorded on the BT. The updated XML is then re-uploaded to the verifier's platform for automatic hash verification and database storage.

Verification. The Verifying Body manages the platform, which interacts with the various actors, and the database where all DP are archived. The platform automatically compares the hash of the current XML file with the hash recorded on the BT. If the hashes match, the update is verified; if not, the update is rejected and flagged for further review.

Public and Private Access. Public Stakeholders can access read-only data from the DP through a web interface developed using a suitable framework. Private Stakeholders can access specific sections of the data relevant to their roles, ensuring that sensitive information is protected while still being accessible to those who need it.

3.2 Computing Layer

The computing layer is fundamental to the framework, enabling the management and processing of complex data to optimize the lifecycle management of ship components. This layer leverages advanced computational techniques and AI to analyze vast amounts of data, providing actionable insights that enhance operational efficiency, regulatory compliance, and sustainability. Building on the data model proposed by Gianvincenzi, M. et al., (2024) the framework can be adapted to the maritime sector through Ship Ecosystem Analysis (SEA). SEA comprises three main components: technological analysis, legislative analysis, and lifecycle analysis, each essential for structuring, populating, and managing the Foundational Data Model (FDM).
The FDM acts as a foundational tree structure data model that can be customized according to the specific requirements of different products and serves as the core element of the DP. It organizes complex product information into a hierarchical structure, considering the products as modular. Its flexibility facilitates interoperability and supports the creation of comprehensive Life Cycle Inventories (LCI) for external environmental lifecycle assessments (LCA), offering new eco-design opportunities. Through the SEA process, the FDM is meticulously defined.

Technological Analysis maps out the complex structure of a ship, identifying its various components and subsystems. This step ensures that the FDM accurately represents all relevant parts and systems. A ship's hierarchical structure includes the Hull, Decks, and Superstructures, each encompassing various critical systems and components. Distinguishing between raw materials, such as steel plates for hull construction, and semi-finished products, like prefabricated bulkheads, is crucial for detailed lifecycle tracking.

Legislative Analysis identifies the regulatory parameters necessary to populate the data model. By examining relevant European and international maritime regulations, such as SOLAS, MARPOL, the European Union Marine Equipment Directive (MED), and the Hong Kong International Convention, the FDM includes all necessary compliance data. These regulations set standards for safety, pollution prevention, equipment compliance, and recycling processes.

Lifecycle Analysis ensures that all stages of a ship's lifecycle are documented and managed within the data model. Various stakeholders populate the data model at different stages, enabling detailed tracking, compliance with regulatory standards, and optimized operational efficiency. The workflow for data population includes material selection, manufacturing, assembly, operation, and end-of-life stages. Each stage involves specific data entry to ensure comprehensive management.

Starting from this structured data model, the computing layer can handle complex parameters derived from technological, legislative, and lifecycle analyses. By leveraging AI, the computing layer optimizes component management in several ways. Initially, simple parameters are collected, such as material properties, usage hours, maintenance records, environmental conditions, and regulatory compliance status. For a ship's hull, these initial parameters might include the type of steel used, its source, hours of operation, maintenance logs, and compliance with safety regulations. AI processes these simple parameters to derive complex parameters that provide deeper insights and predictive capabilities. Analyzing usage patterns, environmental conditions, and maintenance records allows AI to predict the likely failure points of components, facilitating proactive maintenance scheduling. For predictive maintenance, AI would analyze the steel's wear rate, operational stress data, and historical maintenance logs to predict when the hull might require reinforcement or repair. Operational efficiency is enhanced by processing data on component conditions and usage patterns, allowing AI to suggest adjustments to improve performance and extend the lifespan of ship components. Data on fuel consumption, engine performance, and voyage conditions can be analyzed to optimize operational settings and reduce wear and tear. Additionally, AI continuously monitors compliance with safety and environmental regulations, integrating compliance data such as safety equipment status, emission levels, waste management records, and documentation of maintenance activities to ensure adherence to standards. Resource optimization is another significant benefit. AI can optimize the use of materials and energy, minimizing waste and enhancing sustainability. This includes suggesting efficient recycling methods and identifying valuable materials for recovery. AI can analyze material composition, recycling efficiency, and environmental impact to propose optimal recycling strategies. Throughout the ship's lifecycle, data on manufacturing processes, assembly details, operational performance, and end-of-life handling are integrated into the FDM. AI uses this data to provide insights into the most effective lifecycle management practices, ensuring that every stage from design to decommissioning is optimized.

3.3 Data Management Layer

The Data Management Layer (DML) for a general ship production model is crucial for managing data throughout the entire ship life cycle. This layer is responsible for collecting, storing, managing, and analyzing data from different phases and processes of

ship production. The Data Management Layer is crucial to ensure integrated and efficient data management throughout all phases of ship life. Supported by the Computing and Connection Layers, the DML enables optimized operations, improved safety, and regulatory compliance. The components of the DML are different depending on the phase in which it is used.
There are various activities in the design phase, such as: (1) Data collection, which includes CAD/CAM drawings, technical specifications, safety regulations, and customer requirements; (2) Archiving, using databases to store designs, 3D models, and technical documentation; (3) Access and versioning, through version management to track changes and ensure controlled access to data.

Indeed, the construction phase requires: (1) Production planning, with the introduction of enterprise resource planning (ERP) systems to plan and monitor production activities; (2) Monitoring and control, by collecting real-time data through IoT sensors and monitoring systems; (3) Integration, with the provision of linkage with resource management systems (materials, personnel, machinery) to optimize production processes; (4) Operational: (4a) Fleet management, with tracking of vessels through GPS and AIS (Automatic Identification System) systems; (4b) Predictive maintenance, thanks to data analysis and machine learning to predict failures and optimize maintenance activities; (4c) Performance management, through continuous monitoring of operational performance, including fuel consumption and operating conditions; (5) Demolition: (5a) Material tracking, with management of material information for recycling or disposal; (5b) Documentation, in relation to the management of decommissioning data, including inspection reports and compliance with environmental regulations.

The DML, moreover, is connected with other Layers, particularly the Computing Layer and the Connection Layer. The first one enables, on the one hand, data processing, supporting the DML by providing computing capabilities for processing large volumes of data, real-time analysis, and simulations; on the other hand, it allows advanced analytics to be conducted, using machine learning and AI to analyze the collected data and provide useful insights to optimize processes. The second one ensures connectivity between all system components, including IoT sensors, ERP systems and monitoring platforms. It also facilitates system integration by facilitating communication between different systems and platforms, ensuring that data is shared and synchronized efficiently. Finally, it is responsible for security, enabling the implementation of security protocols to protect data during transmission and access.

As also pointed out in (Bronson et al., 2024), the lack of a consistent understanding of a ship product's data model, from design to operations, is currently a limiting factor in the implementation of more efficient ship lifecycle management and design processes. This calls for useful reflection to understand how current the topic of Ship Data Model evolution is with respect to computational data model paradigms. In fact, Bronson et al., 2024 brings out how only recently there has been the release of specific recommended practices DNV, 2023 to optimally manage the reliability of DTs, addressing all phases from conception to product operation. This is because the DML allows the DT ecosystem to be perimetered through various layers, starting right from the DML.

3.4 Connection Layer

In the context of building a ship, the Connection Layer plays a key role in ensuring that all components and systems communicate effectively throughout the ship's lifecycle, from design to demolition. There must be Collaboration and Integration: during the design phase, the Connection Layer facilitates collaboration between different engineering and design teams. Using data management platforms and 3D modeling tools (such as CAD), design data can be shared and updated in real time, ensuring that all changes are immediately visible to all parties involved. This Connection Layer manages data flows between the various software used for design and other phases of the ship's life cycle. During the construction phase, automation and control dictate that the Connection Layer manages communications between automated construction equipment, such as cranes and welding robots. This allows remote control and real-time monitoring of construction activities, improving efficiency and reducing downtime. For example, sensors installed on equipment can send status data and diagnostics to central systems, enabling timely interventions in case of problems.

In the operational phase of the ship, there is a need to focus on navigation and cargo management; once the ship is operational, the Connection Layer maintains communications between the navigation and cargo management systems. These systems need to continuously exchange data to ensure that the ship is following the optimal course, and that the cargo is properly distributed to maintain the stability and safety of the ship. Crucial, again in this phase, is monitoring and maintenance: sensors distributed throughout the ship constantly monitor the status of various components, such as engines, cooling systems, and hull structures. The Connection Layer then becomes responsible for collecting this data and sending it to predictive maintenance systems, which can predict failures and plan preventive maintenance actions, thanks to the construction of machine learning algorithms that can be collectors of data collected on more than one ship in the reference fleet.

In the last phase of scrapping, there is the management of historical data. At the end of the ship's life cycle, the Connection Layer facilitates the collection and analysis of historical data regarding the ship's construction, operation, and maintenance. This data can be used to improve future design and construction processes, and to ensure that demolition takes place in a safe and environmentally compliant manner. Thanks to such historical data, it is also possible to predict, through external monitoring of specific commercial and market parameters (in turn analyzed and integrated on specially defined machine learning systems), a residual value of the ship that is to be scrapped, as a complex system consisting of a series of parts, in turn made of certain materials, that follow a specific market with quotations that could be appropriately determined with precision from a predictive perspective and in line with the timeframe for dismantling and recycling the same materials. Therefore, the complex system of a ship is transformed, at the end of its life, into a digital model that gathers all essential characteristics.

As with the DML, the Connection Layer must also integrate with the Computing Layer that provides the computing power needed to process the data collected from the various systems and sensors. This layer, as mentioned earlier, uses machine learning and data analysis techniques to improve the accuracy of maintenance predictions and optimize ship operations.

The role of the Connection Layer becomes indispensable in ensuring the smooth and secure communication required for all systems involved in the construction and operational activities of a cargo ship. This necessity arises from the need to improve efficiency, enhance safety, and maintain reliability throughout the entire lifecycle of the ship.

3.5 The specific role of AI integrated into the DT

A framework for the shipping sector that integrates Digital Twin, AI, and IoT enables the creation of a real-time virtual model of ships, replicating their physical behavior and improving efficiency and safety. IoT sensors installed on ships and port infrastructure collect real-time data on various parameters (e.g., weather conditions, engine status, wear and tear), which AI algorithms analyze to optimize routes, predict maintenance, and reduce energy consumption.

IoT sensors monitor structural integrity and system performance, while NFC/RFID technologies ensure component traceability and operational security. For example, IoT sensors can be placed along the hull to monitor deformation, corrosion, water pressure, and structural integrity. The collected data helps detect any damage or wear over time, allowing maintenance to be planned. RFID devices can be strategically placed on the hull to identify and track specific components, such as panels and welds, facilitating the monitoring of their condition over time and lifecycle management. In propulsion systems and the engine, IoT sensors for temperature, pressure, vibration, and fuel consumption monitor engine performance in real-time, identifying potential failures or inefficiencies. This data is essential for the Digital Twin, which can simulate performance and suggest optimizations. NFC/RFID devices and related tags can be used to identify engine components such as pistons, shafts, and filters. The ship's beams and supporting structures can be monitored by sensors detecting mechanical stress, torsion, and vibrations. This data helps assess the ship's structural integrity in the Digital Twin, preventing structural failures. RFID sensors are placed on beams and other structural components to facilitate their identification and maintenance, helping to maintain an accurate record of quality control and maintenance operations. The ship's deck can be equipped with a wide range of IoT sensors that monitor weather conditions, ship stability, GPS position, and speed.

3.6 The benefit of integrating AI to DT in the circular economy

The integration of AI with data collected from IoT sensors on board a ship, in combination with DTs, represents a powerful tool for optimizing naval operations and supporting circular economy practices. Through automated models based on machine learning algorithms, AI can analyze this data to identify patterns and anomalies that may signal the onset of problems, such as an abnormal increase in vibrations, indicative of engine component wear, as well as consumption predictions at different speeds. AI can predict when a component is at risk of failure, enabling scheduled maintenance before a problem occurs, improving the ship's reliability and reducing waste associated with emergency repairs. Additionally, AI can monitor the lifecycle of components on board, suggesting optimizations in the use of these resources. It can also identify components or materials that, instead of being discarded, can be recycled or reused in other parts of the ship, in other ships of the fleet, or even resold. This process is supported by RFID or NFC tags that track the usage history and composition of materials.

Another challenge that AI can effectively address is corrosion management. Thanks to IoT sensors, which detect indicators such as pH, temperature, humidity, electrical potential, and the presence of chlorides or dissolved oxygen, AI can analyze data in real-time and identify patterns and trends that could indicate an acceleration of the corrosion process. AI also plays a crucial role in assessing the residual value of a ship after many years of service, integrating internal operational data with external contextual information. This advanced approach offers an accurate and dynamic estimate of the ship's value, considering not only its technical condition but also economic, regulatory, certification, and market factors. These valuations can be dynamically updated with new data, reflecting current market and ship conditions, and allowing for the simulation of different scenarios such as selling, scrapping, or recycling, evaluating the impact of each on the residual value. This approach significantly contributes to the creation of a market based on the circular economy, optimizing resource use, reducing waste, and maximizing the residual value of ships and their components. AI, supported by DT and IoT data, facilitates the reuse, recycling, and regeneration of materials, integrating sustainable practices and improving overall efficiency. This system can extend the useful life of ships, adding value throughout the entire lifecycle.

However, it is important to emphasize that the use of IoT and AI should always be subject to human oversight, especially regarding navigation safety and control. From this perspective, machine autonomy performs specific tasks, while human autonomy manages supervision, particularly in conditions of changing external factors and uncertainty.

4 Discussion and Conclusion

Proposing an integrated system of digital technologies for ship management is complex due to the nature and volume of data involved. Hatledal et al., 2020 as already developed a framework for DT's maintenance management on the hull, integrating AI to predict pressure and stress states. The technical implementation of an integrated system to assess the residual value and condition of a ship requires a multidisciplinary design that involves hardware, software, network infrastructure, data science, and maritime industry expertise. The schematic shown in Fig. 3 represents one approach to integrating the key components necessary for creating a framework aimed at determining the residual value of a ship using AI, IoT, and DT. This schematic illustrates how data flows through the various system components, from acquisition via IoT sensors to local and cloud processing and DT management, and finally to visualization through dashboards and user interfaces, with further enrichment from external contextual data.

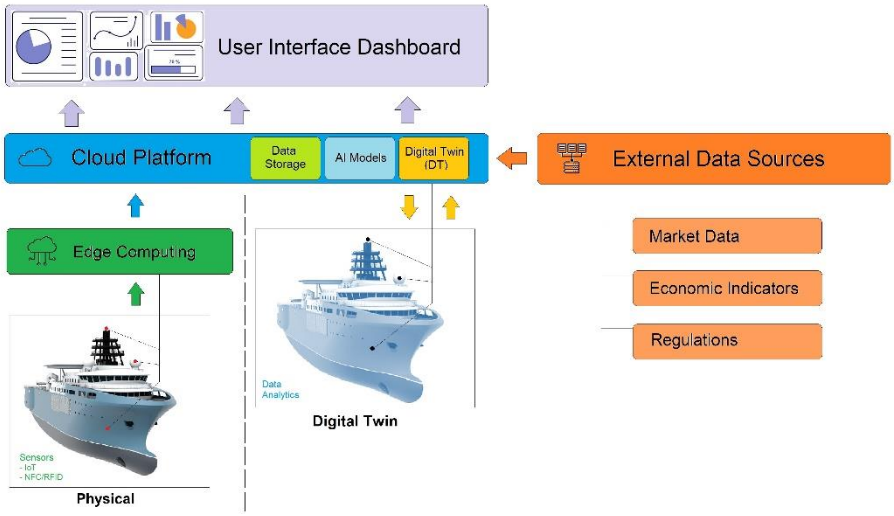

Figure 3 Diagram of Components of the AI-DT-IoT Framework

The DT model of the ship must then be created using CAD and simulation software, continuously updating real-time data. Machine learning models, such as neural networks and random forests, are trained on historical data to predict the deterioration of various ship components and to assess the risk associated with continuing operations without maintenance interventions. Meanwhile, regression models and predictive analysis can be used to estimate the ship's residual value, based on market data, economic trends, and regulations, integrating external contextual data via APIs, such as market conditions, exchange rates, material prices, and environmental regulations. Part of the data processing can be done directly on board, using edge devices that reduce latency and ensure continuous operations even with intermittent connections, while intensive processing, such as AI model training and Digital Twin simulations, is carried out in the cloud to leverage scalable resources. Data analytics platforms provide interactive dashboards for operators, allowing them to monitor the ship's status, failure predictions, and estimated residual value in real-time. AI can generate automated periodic reports, updating ship owners and operators on the ship's condition and offering maintenance suggestions.

The end result is an intelligent and adaptive ecosystem that not only optimizes ship operations and maintenance but also provides a dynamic and accurate assessment of its residual value, supporting strategic decisions based on real and contextual data. This work highlights the fundamental role of an advanced framework within a DT ecosystem, seamlessly integrated with the latest digital technologies, which have been at the forefront of technological innovation in recent years. This integration is specifically aimed at supporting the increasingly necessary paradigm of the circular economy. The key technologies identified as most effective for this purpose include BT, SCs, IoT devices, and DTs. When integrated, these technologies are effectively managed through sophisticated machine learning algorithms derived from AI.

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